Using Side Scan Sonar for Relative Navigation

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Abstract- **This paper describes the interaction between the kinematic model of the AUV MARES, and the measurement and observation of the environment through images obtained with the sonar use. Three types of Sonar are discussed in this paper; there are forward-look, side scan and multibeam. But the sonar used to develop this work was the side scan sonar. The type of observations and characteristics of the environment provided by the sonar are described here. The method, which connects the sensory part of the vehicle with the observations of the sonar, was the Kalman filter (EKF). In this paper, are presented two simulations of filters for two different characteristics. Both filters estimate the characteristics of natural landmarks, creating an environment map, but both of them consider different states of the vehicle. Results of the simulation are obtained. The features that are considered are an underwater pipe on the floor and a wall. It also generated a control for the vehicle that provides the capacity to move along the feature/landmark from a reference distance.**

I. Introduction

Some vehicles, such as ROVs (Remotely Operated Vehicles) are not able to navigate without power cable. Other vehicles such as AUVs (Autonomous Underwater Vehicles) are not able to navigate without the help of methods like absolute location, such as GPS (Global Positioning Systems) or acoustic beacons. In fact these vehicles have a certain degree of autonomy, but cannot be considered as truly autonomous [1],[2],[3],[4] and [5].

The true definition of autonomy is the capacity that the vehicle has to move and locate in the world, independently, with the maximum certainty of localization and without environment preparation [6]. One of the fundamental characteristics of autonomy is also the capacity of the vehicle moving without bounds, often introduced by methods such as acoustic beacons, which have a maximum range.

It is this definition of autonomy that is the opportunity of this work. The fundamental aim is to equip the AUV MARES [3] with real autonomy, by using side scan sonar, allowing it to navigate relative to landmarks in the marine environment, such as pipes and walls.

The importance of providing higher degree of autonomy to vehicles appears because the use of AUVs has had rapid growth on civil life, military or services in recent years.

In section II sensors and navigation methods problem are described. The third section describes sonar data, and a computational method to extract the features, while in the fourth section two navigation filters for two different features are presented. In section V AUV guidance and control are described. In section VI simulation results are presented. Finally in section VII project limitation are described.

II. Underwater Vehicles Autonomy

The autonomy in ocean robotic is divided into the following three levels, [5]:

Self-energy: Provide a vehicle own sources of energy.

-Self-navigation: represents the capacity of the vehicle to navigate accurately with a low error of estimation. This type of autonomy is the fundamental core of this paper.

-Autonomy of decision: this is the ability to decide and act in various scenarios.

A. Evolution of Autonomy in Underwater Robotics

Different sensors and techniques for localization of vehicles are described in [7]. These sensors and techniques are divided into absolute and relative localization.

Dead-reckoning sensors, such as inertial navigation (INS), attitude sensors, digital compass, Doppler-effect sensor (DVL) are relative sensors of localization in space. The position of the vehicle in the world is given by the sum of successive estimated position differences, leading to a position error that grows without bounds.

In the absolute localization at each instant of time the position of the vehicle in the world is estimated. Some methods of absolute localization are based on active beacons, such as acoustic beacons LBL (Long baseline), ULBL (Ultra long baseline) and SBL (Short Baseline) and Global Positioning System (GPS or DGPS).

The methods based on acoustic beacons and the GPS involve high errors of localization [7]. Then the need of terrain-based navigation methods, which combine the relative and absolute navigation methods and the landmarks existing on the sea environment, appears.

B. SLAM-Simultaneous Localization and Mapping

The terrain-based navigation [8], based on natural landmarks has essentially two phases:

-Construction map, knowing the localization of the vehicle in the world by other methods of localization.

-Localization of the vehicle based on the world map constructed a priori.

The aim of this work, using side scan sonar and using the sensors of attitude and dead-reckoning installed on the vehicle, is join the two stages of the terrain navigation on a single stage, allowing the vehicle to construct the map and to locate itself simultaneously. This is a problem of SLAM (Simultaneous Localization and Mapping) or CLM (Concurrent Localization and Mapping).

SLAM and CLM, both problems have the same objective and give true autonomy to the AUV. The problem of SLAM is treated in [6], applied on AGVs (Autonomous Guided Vehicles), while CML is treated in [8] on AUVs.

With the resolution of SLAM/CML the AUV will have autonomy and can be launched on missions to search and collection of data with minimal preparation, without bounds of navigation and with a great certainty of position estimation.

To make the interconnection of relative navigation methods, dead–reckoning, with observations obtained by sonar, a method as the Kalman filter is needed.

The Kalman filter, more precisely EKF (Extended Kalman Filter), described in [10], consists of a Kalman filter in which the state vector consists not only on information about the vehicle (its position), but also on information detected and identified from natural landmarks. Thus, the estimation will be not only the vehicle but also the environment, which in fact results on a SLAM problem. The approach described here follows the ideas from [6], [8], [9], [11] and [12] where Kalman filters are also employed.

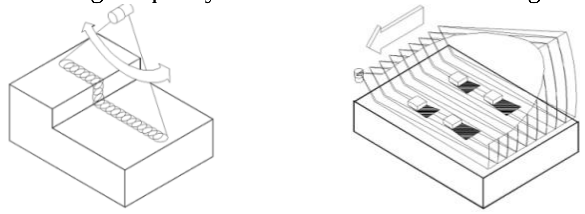
III. Sonar Data

A. Sonar, SOund Navigation And Range

Sonars can be used to obtain acoustic images of the sea bed allowing the extraction an identification of natural landmarks.

The forward-look sonar makes several observations of the environment causing overlap of the sea bed [8]. This sonar provides little information and the measurement noise is high, generating acoustic images of poor quality.

An image obtained by the acoustic side scan sonar is the echo of lines of force in time, equally spaced between them. In [8], is said that the acoustic images obtained by side scan sonar have higher quality than forward look sonar images.



a) b)

Fig. 1 a) Forward-look scan. b) Side scan Scan.

In both them, [8] and [9], the sonar type chosen to development of the work was the side scan sonar. In this work the chosen sonar was also side scan sonar, more precisely, the Imaginex Sportscan, that is shown in Fig. 2.

Fig. 2 Side scan Imagenex Sportscan

The multibeam corresponds to the sonar type in which the quality of acoustic image obtained is higher than the both others. The information collected is larger, which allows terrain-based navigation of higher quality.

The multibeam sonar, gives a three-dimensional pictures of the environment. It is composed by an array of sonars (multi-beam), arranged in the same direction and angle of incidence fixed, known and that differs between them.

B. Obtained Data by Analisys of Acoustic Image

For a feature located at the sea floor, the analysis of an acoustic image provides important data required for the navigation procedure described here. That data are:

-The size of the no-echo zone, (H) allows us to know the height above the floor at which the AUV is.

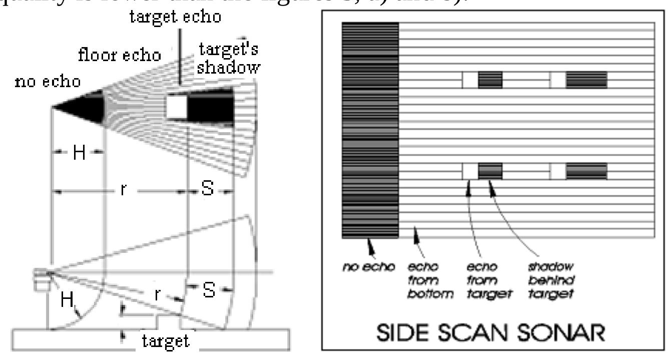
-A sum of no-echo zone with the area of the bottom echo and the target, (H + r), allows to know the distance between the submarine and the target.

-A shadow zone of the target (S), where there is no-echo, lets us know the height of the target. This height is given by the expression:

$$h = \frac{H.S}{r+S} \tag{1}$$

All these characteristics can be obtained by image processing algorithms.

The algorithms of segmentation and features extraction should be flexible and then be able to handle images whose quality is lower than the figures 3, a) and b).



a) b)

Fig. 3 a) Beam observation, Target values (H, r, h and s). b) Side scan ideal image.

C. Acoustic Image extraction

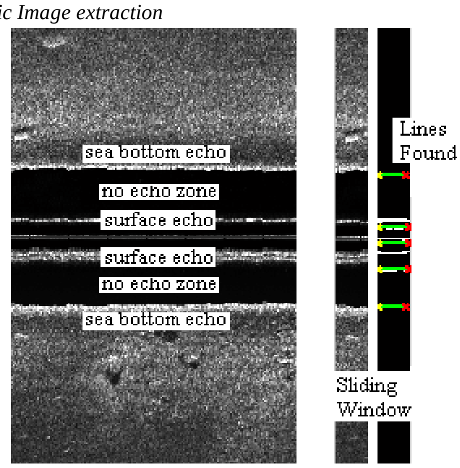


Fig. 4 Acoustic image acquired (left), sliding window (middle), features extraction (right).

An example from acoustic image segmentation is shown in Fig. 4. In that case the acoustic image obtained (left) shows the perception of the sea bed. Is possible see when the echo from the floor appears. Each vertical line (slice of image) is a ping of 500 points that side scan acquired. The extraction of features, which in that case only correspond to sea floor, was made using a sliding window (Fig.4 middle) with fixed size. Using sliding window possible disturbances in image can be despised. Thus, in each sampling instant, the observation will be the new slice acquired by side scan, added to the others slices, according sliding window size.

Thus, at each observation time, a sliding window is built for later segmentation and features extraction.

The image extraction and segmentation results are shown by Fig.4 (right). The results obtained are the lines equations on the sliding window. It can be seen that all relevant lines are detected, such as sea floor, starboard and port, and also the lines corresponding to surface echoes.

To obtain sea floor and surface echo lines, a sequence of image operations are applied. These operations are a bimodal threshold, for binary image result, followed by horizontal edge detection that can be a first or second derivate mask. Finally, the Hough transform is employed to obtain the equation lines. All these image methods and computational processes can be seen on [13], [14] and [15].

IV. NAVIGATION FILTERS

A. Kalman Filter: State (East, South, Depth)

To estimate the position of the vehicle two reference frames are considered: a static world fixed frame and a moving frame attached to the vehicle [16], as shown in Fig.5.

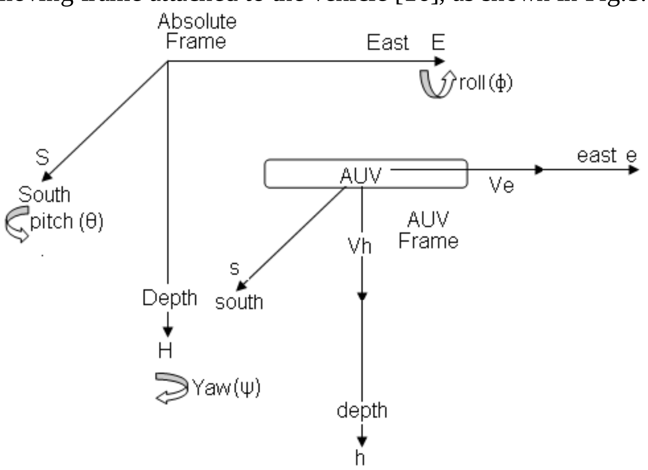


Fig. 5 Absolute frame and AUV frame

Considering a straight line feature characterized by a line of slope (m) and origin intersection (b), on sea bed, the process model of the filter will be given by a non linear system in continuous time. The state vector is:

$$x = [E_v \quad S_v \quad H_v \quad m \quad b]^T \tag{2}$$

The linear speed of the vehicle only exists in two directions, east (e) and depth (h) axis. The kinematic model of the vehicle will be given by:

$$\dot{x}(t) = \begin{bmatrix} c\,\psi(t)\left(c\,\theta(t)\,V_e(t) + s\,\theta(t)\,V_h(t)\right) \\ s\,\psi(t)\left(c\,\theta(t)\,V_e(t) + s\,\theta(t)\,V_h(t)\right) \\ -s\,\theta(t)\,V_e(t) + c\,\theta(t)\,V_h(t) \\ 0 \\ 0 \end{bmatrix}, \tag{3}$$

where $c(\cdot)$ is $\cos(\cdot)$, and $s(\cdot)$ is $\sin(\cdot)$. Along this paper that notation will be used.

The input vector u(t) and the Gaussian white noise w (t), with mean zero, associated with each input, are represented by:

$$u = [V_{ev} \quad V_{hv} \quad \theta_v \quad \psi_v]^T, w = [\epsilon_{Ve} \quad \epsilon_{Vh} \quad \epsilon_{\theta_v} \quad \epsilon_{\psi_v}]^T \tag{4}$$

$$E[w(k)] = 0 \; and \; E[w(k)w^T(k)] = Q \tag{5}$$

1. Sonar Observation: Feature Pipe.

Each time instant, the vehicle, detect a point of the pipe on its frame. Then each observation is the point:

$$Xi = [e_T \quad s_T \quad h_T]^T = \left[0 \quad \sqrt{r^2 - {h_T}^2} \quad H\,c\beta\right]^T, \tag{6}$$

where r and H are obtained through the acoustic image, and are shown in Fig.3 a). β is the angle that the sonar beam makes with the line orthogonal to the floor plan, Fig.8.

The line equation in the world reference frame is equal to:

$$S = mE + b \tag{7}$$

The point Xi in world coordinates its equal:

$$X_{World} = x_v + R_v X_i, \tag{8}$$

where R_v is the rotation matrix from the AUV to world frame. That matrix is given by:

$$R_v = \begin{bmatrix} c\,\psi\,c\,\theta & -s\,\psi & c\,\psi\,s\,\theta \\ s\,\psi\,c\,\theta & c\,\psi & s\,\psi\,s\,\theta \\ -s\,\theta & 0 & c\,\theta \end{bmatrix}, \tag{9}$$

Thus, the coordinates of the world represented in the coordinates of the submarine are:

$$Xi = {R_v}^{-1}(X_{world} - x_v) \tag{10}$$

Through (7), (8), (9) and (10) equations, the estimated s_T is given by:

$$s_T = \frac{m(Ev + h_T\,c\,\psi_v\,s\,\theta_v) - h_T s\,\psi_v\,s\,\theta_v + b - S_v}{c\,\psi_v + m\,s\,\psi_v} \tag{11}$$

The estimated h_T, is equals to:

$$h_T = \frac{H_v}{c\,\theta_v} \tag{12}$$

So the estimated value of H is given by the following expression:

$$H = \frac{H_v}{c\,\theta_v\,c\,\beta} \tag{13}$$

The observation noise is represented by a zero mean vector and covariance error R:

$$v = [\epsilon_{s_T} \quad \epsilon_H \quad \epsilon_{\psi_v} \quad \epsilon_{\theta_v}]^T \tag{14}$$

$$E[v(k) = [0] \; and \; E[v(k)v^T(k)] = R, \tag{15}$$

where ϵ_{ψ_v} and ϵ_{θ_v} are due to error measurement of the AUV yaw and pitch, and ϵ_{s_T} and ϵ_H are derived from the measurement of s_T and H in the acoustic image.

Therefore, the observations of the filter are given by the expression:

$$z(k+1) = \begin{bmatrix} s_T + \epsilon_{s_T} \\ H + \epsilon_H \end{bmatrix} \tag{16}$$

B. Kalman Filter: State (Distance, Depth)

The vehicle state will be defined by the distance of the vehicle to the feature, by the depth coordinated of the vehicle, i.e. the relative height to the sea floor, and the orientation of the feature in the world reference frame. Thus, the state will be:

$$x = [D \quad H_v \quad \gamma]^T \tag{17}$$

Taking into account the sea currents in the east and south axis (c_e) and (c_s), the speed of vehicle (V_e) and (V_h), assuming a roll (Φ) close to zero, and finally taking into account the yaw (ψ) and pitch (θ) angles, we have:

$$\dot{e}_v = \mathrm{c}\,\theta(\mathrm{t})\, V_e(t) + \mathrm{s}\,\theta(\mathrm{t})\, V_h(t) \tag{18}$$

$$\dot{h}_v = \mathrm{s}\,\theta(\mathrm{t})\, V_e(t) - \mathrm{c}\,\theta(\mathrm{t})\, V_h(t) \tag{19}$$

The system input is $u(t)$ and $w(t)$ is the white noise. There are the following vectors:

$$u(t) = [V_e \quad V_h \quad \psi \quad \theta \quad c_e \quad c_s]^T \tag{20}$$

$$w(t) = [\varepsilon_{Ve} \quad \varepsilon_{Vh} \quad \varepsilon_{\psi} \quad \varepsilon_{\theta} \quad \varepsilon_{ce} \quad \varepsilon_{cs}]^T \tag{21}$$

$$E[w(k)] = 0 \ \ and \ E[w(k)w^T(k)] = Q \tag{22}$$

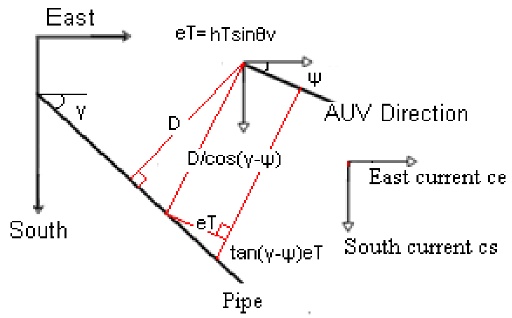


Fig. 6 Distance (D) between AUV and pipe.

Through figure 6, the approximation speed from the vehicle to the pipe can be computed, and is given by:

$$\dot{D} = \mathrm{s}(\gamma - \psi) \cdot (V_e\, \mathrm{c}\,\theta + V_h\, \mathrm{s}\,\theta) - c_s\, \mathrm{c}\,\gamma + c_e\, \mathrm{s}\,\gamma \tag{23}$$

1. Sonar observations: Feature pipe

In this case, we use three observations: the minimum and maximum distance of the vehicle to the pipe, $(Dmin, Dmax)$ and finally the detected distance, in the acoustic image, between vehicle and the sea bed (H).

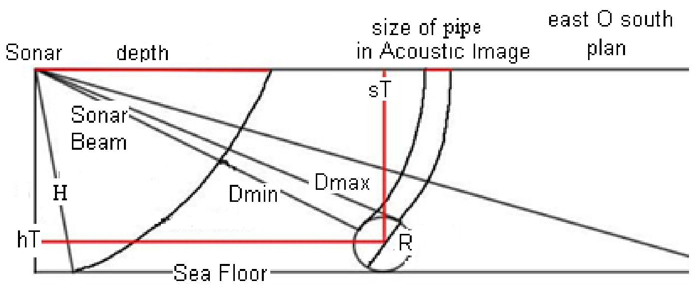


Fig. 7 Three observations, Dmin, Dmax and h. Size of pipe in the image.

The minimum distance is related to the system state as follows:

$$Dmin = -R + \sqrt{{h_T}^2 + {s_T}^2} \tag{24}$$

The maximum distance, taking into accounts that the sonar ever sees approximately a circle, is related with the state the following way:

$$Dmax^2 = R^2 + {h_T}^2 + {s_T}^2 \tag{25}$$

Finally, the third observation H already was computed in previous (13).

The expression for s_T, also already been computed (11), in order to other states, $E_v, S_v, H_v, m\ e\ b$, it will be again compute, now in order to $D, H_v\ e\ \gamma$ states.

$$s_T = \frac{D}{\mathrm{c}(\gamma - \psi)} + \tan(\gamma - \psi)\tan\theta_v\,(H_v - R) \tag{26}$$

Also h_T was been calculated in previous (12), but it differs when radius pipe, R, is considered. So h_T come:

$$h_T = \frac{H_v - R}{\mathrm{c}\,\theta_v} \tag{27}$$

Thus, the filter observation is given by:

$$z(k+1) = \begin{bmatrix} Dmin + \epsilon_{Dmin} \\ Dmax^2 + \epsilon_{Dmax^2} \\ H + \epsilon_H \end{bmatrix} \tag{28}$$

2. Sonar observation: Feature wall

The wall will be seen by the sonar as a growing strength echo from the minimum distance between the submarine and the wall.

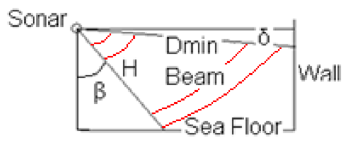


Fig. 8 Two observations, Dmin and H, when the feature is a wall.

The filter observation will be formed by the following two characteristics:

$$z(k+1) = \begin{bmatrix} Dmin + \epsilon_{Dmin} \\ H + \epsilon_H \end{bmatrix} \tag{29}$$

First observation, $Dmin$, is determined geometrically by examining figure 9:

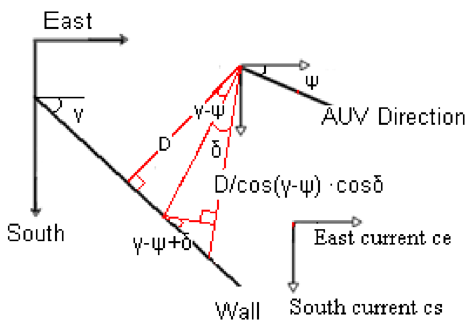


Fig. 9 Distance (D) between AUV and wall.

Resulting in:

$$Dmin = \frac{D}{\mathrm{c}(\gamma - \psi)} \cdot (\mathrm{c}\,\delta + \mathrm{s}\,\delta \tan(\gamma - \psi + \delta)) \tag{30}$$

V. AUV Guidance And Control

To assess the performance of the developed navigation algorithms, we simulated the whole system with synthesized acoustic images. AUV guidance and control loops were designed to ensure that the AUV could follow the detected feature.

The fundamental aim is to make the vehicle follow a path parallel to the feature, either the wall or pipe, at a given reference distance Dref. The output of the control is the yaw rate.

The control consists of two PIDs, the first is function of the distance $f(D - Dref)$ while the other PID is function of difference between the feature and yaw vehicle angles $f(\gamma - \psi)$. The two PIDs have therefore contrary effects; one tends to increase the relative angle between vehicle and feature. The other tends to decrease this angle. Thus, the second PID is of lower magnitude than the first.

A. *Determination of control gains*

The system is not linear and that prevents us from obtaining the control gains in the same way as the linear systems are obtained.

Nonetheless, since the fundamental purpose for this paper is not the application of guidance laws, we followed a somehow empirical procedure for the determination of the control gains.

For different speeds of vehicle motion, the path control should be higher when the linear speed is higher for the same vehicle behavior and trajectory.

The demonstration of this result is made below. The yaw rate is given by:

$$\frac{d\psi}{dt} = \frac{d\psi}{ds} \cdot \frac{ds}{dt} = \frac{d\psi}{ds} \cdot v, \tag{31}$$

where s is the path followed, and $\frac{ds}{dt}$ is the linear speed of the vehicle. Then:

$$\frac{d\psi}{ds} = \lim_{\Delta s \to 0} \frac{\Delta\psi}{\Delta s} = curvature(k) = \frac{1}{R}, \tag{32}$$

where R is the radius of curvature of the vehicle trajectory. Thus, for a given curvature, the speed of rotation of yaw will grow proportionally with the linear speed of the vehicle.

The control only enters into effect when distance between the feature and the vehicle it is below a certain threshold (T).

For greater distances than T, the vehicles approaches the features with a predefined angle (α). Thus, the initial value of the yaw rate control is given by:

$$\dot{\psi} = (T.mdist - \alpha.mang)v, \tag{33}$$

where v is the vehicle linear speed.

Considering only the distance proportionally constant, $mang$ equals to zero, for a desired curvature equals to k_{dist}:

$$mdist = \frac{k_{dist}}{T} \tag{34}$$

Considering now the equation (33), and constant proportional to distance (34), the angle constant proportional, for a desired curvature of k, is:

$$mang = \frac{k_{dist} - k}{\alpha} \tag{35}$$

So the expression of control path is given by:

$$\frac{d\psi}{dt} = \big(mdist(D - Dref) - mang(\gamma - \psi)\big)v \tag{36}$$

VI. Simulation Results

A. *Kalman Filter: State (Distance, Depth)*

The simulation time corresponds to a displacement of the vehicle during 3 minutes. In acoustic sensor and the image obtained is introduced random error with mean zero like the reality.

The sensors simulated are the digital compass that measures the yaw, pitch and roll of vehicle on the world frame.

TABLE 1
Simulation Parameters.

Feature	Wall	Pipe
East/depth Speed (m/s)	0.5/0	1/0
East/South Corrent(m/s)	0/0	0.3/0.3
True Orientation (Degrees)	15	30
Reference Distance (meteres)	7	6

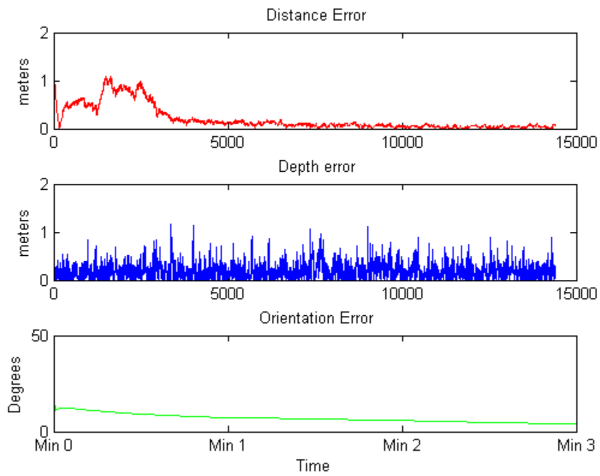


Fig. 10 Simulation when the feature is a wall, state error. It can be seen that error goes to a stationary small error.

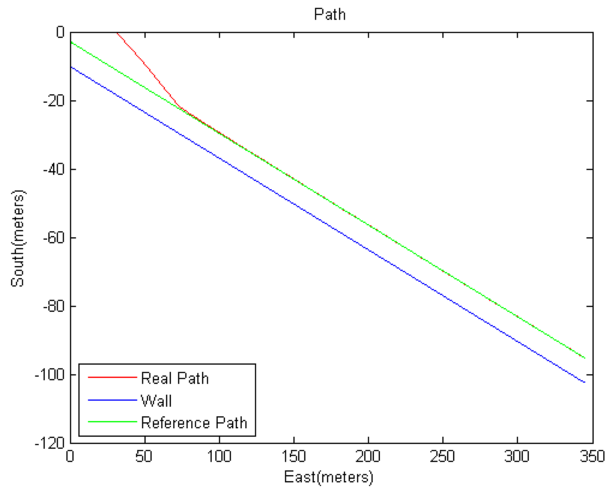


Fig. 11 Simulation when the feature is a wall, real and reference path that is a 7 meters parallel path between AUV and the feature.

Also the sea currents measures were simulated, the east and depth speed. On all that measurements over-dimensioned errors are introduced.

All vehicle sensors have a 20Hz sample rate, while the observation by sonar was simulated for a 5Hz sample rate.

The distance error (between a wall and the AUV), Fig.10, in steady state is around 15 cm. The error of maximum depth reached is about 1 $meter$. The error of angle at steady state goes to 0.

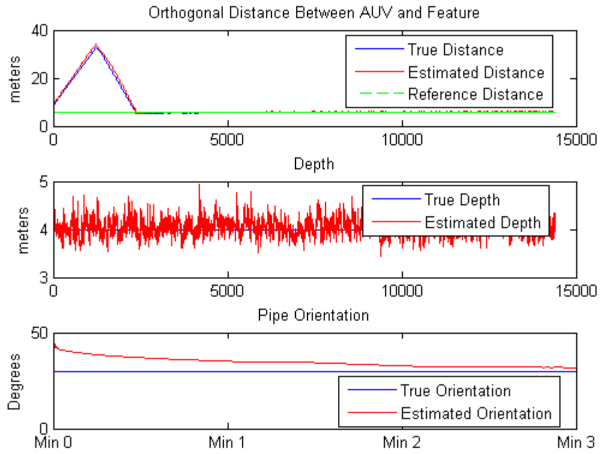


Fig. 12 Simulation when the feature is a pipe. Estimated State and the true state, both are close.

Figure 11 shows the reference and real path that AUV follows. Can be seen that both are very close. This is due the fact of the described filter provide a good estimation. That also proves that the dimensioned control works.

The figure 12 represents the three states. The real state and estimated are very close.

B. Kalman Filter: State (East, South, Depth)

This filter was also simulated. The conclusions reached were that this is a type of filter that is not suitable for relative navigation. In fact, when the state variables are the east and south coordinates in the world reference frame, the co-variance of these two states grows without bounds. As the error of the state is unbounded at a given instant time the accuracy of the estimated state is no reliable. This happens because the sonar provides information of relative distance of the vehicle to a feature, but does not provide information of the position at which the vehicle is in the feature. Only when the feature is parallel to east there is a guarantee that the error of estimation of the south state converges, but the east state error grows with no bounds.

VII. Project Limitations

The acoustic image is sensible to disturbances caused by the water dirt or by particles suspended inside the water. This can make difficult image processing.

When the goal is follow a parallel path at a reference distance from a feature the sonar need to see for all instants of time the feature. Thus, the sonar should never lose the feature in the image.

When the objective is control the vehicle trajectory based on image seeing provided by sonar all should be autonomous, what requires well structured environments.

VIII. Conclusions

This paper describes a method for the estimation of the position of the vehicle and simultaneous map building. The method is based on Extended Kalman Filter.

Positioning data is provided by side scan sonar and environment observations from two different features of the marine environment are considered: a pipe and a wall. This paper shows how can be integrated the information from the sensory part of the vehicle, which makes successive errors and leads the estimation state error to a unbounded error, with the observation of the environment, used to reduce the error of estimation, ever that an observation are obtained.

The control for the vehicle follow a path parallel to the feature is successfully applied on simulation.

This article demonstrated the operation of two filters, and concluded that one of them is suitable for relative navigation and another not. Thus, the filter in which the vehicle state is the distance to the feature, the distance to the sea floor and orientation of the landmark, is the ideal filter and ensures a good estimation.

An interface in C++ has been developed for communication between the AUV and Imagenex SportSan sonar. In future it is intended to apply the filter to the AUV MARES as the control path, and for that real acoustic images with real features will be obtained, processed and segmented in order to obtain the observations and features values.

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